

# LEARNING CURVES FOR ENERGY TECHNOLOGY: A CRITICAL ASSESSMENT

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## Abstract

In this paper, which forms a chapter in the forthcoming Book “*Delivering a Low Carbon Electricity System: Technologies, Economics and Policy*”<sup>†</sup>, Jamasb and Köhler revisit the literature on learning curves and their application to energy technology and climate change policy analysis and modeling. The academic literature and policy documents have in recent years embraced the learning curves and applied the concept to technology analysis and forecasting cost reductions. We argue that learning curves have often been used or assumed uncritically in technology analysis and draw parallels between the use of learning rates in energy technological progress and climate change modeling to that of discount rates in social cost benefit analysis. The paper discusses that care needs to be taken in applying learning curves, originally developed as an empirical tool to assess the effect of learning by doing in manufacturing, to analysis innovation and technical change. Finally, we suggest some potential extensions of learning curves, e.g. by incorporating R&D and diffusion effects into learning models, and other areas where learning curves may potentially be a useful tool in energy technology policy and analysis.

Keywords: Energy technology, electricity, technical change, learning curves

JEL Classification: O3, Q4

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## 1. Introduction

One of the main drivers of current energy policy and research is the climate change issue. Climate science suggests that there is a need to drastically reduce greenhouse gas emissions (GHGs) and one of the main sources of GHGs is the combustion of fossil fuels for electricity generation. This has in turn led to efforts to develop low-carbon technologies to reduce the emissions. The policy problem now is how to transform the electricity system to introduce these new technologies and support their large scale diffusion. Hence innovation and technical change are at the centre of climate change and energy policy debate.

Technical change is a gradual process and evolves through different stages. A well-established account of this is Schumpeter's invention-innovation-diffusion paradigm (Schumpeter, 1934; 1942). Within this framework, invention refers to the generation of new knowledge and ideas. In the innovation stage, inventions are further developed and transformed into new products while diffusion is the widespread adoption of the new products. Later, Solow (1957) attributed the unexplained element of increased productivity growth of the economy to technical change. At this time, the literature still viewed technical change as an exogenous factor to the economy.

In recent years, there have been considerable developments in macroeconomics and energy economics, both theoretical and empirical, on the theme of technical change. The focus of the literature has shifted to the role of economic factors on technical change (Thirtle and Ruttan, 1987). These changes have primarily been in the new macroeconomic endogenous growth literature and the application of the learning curve management literature to microeconomic analysis including in the energy sector. As a consequence, there has been a transition in the climate change and energy literature, such that endogenous technical change (ETC) is now a major feature of many analyses (Köhler et al., 2006).<sup>1</sup>

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<sup>1</sup> ETC, where technical progress is dependent upon variables and processes within the model, leads to possibilities for policy to induce technical change (ITC) by influencing these processes. If ETC is included, policy operates through the ETC mechanisms of the model to generate ITC that would not otherwise occur. This is in contrast to exogenous or autonomous technical change, often represented through the autonomous energy efficiency improvement (AEEI) in climate-economy models.

In the microeconomic context, learning curves emerged as an empirical method for analysis of the effect of learning on technical change. They measure technical change as cost (or an input factor) improvement of a product or technology as a result of learning. Learning as a distinct source of technical change was presented in Wright (1936) and Arrow (1963) and is often termed as “learning by doing”. The learning effect is measured in terms of reduction in the unit cost (or price) of a product as a function of experience gained from an increase in its cumulative capacity or output.

Early applications of learning curves, between 1930s and 1960s, were mainly production orientated (Wright 1936; Hirsh, 1952). In 1970s and 1980s, they were also used in business management, strategy, and organisation studies (BCG, 1970; Argote and Epple, 1990).

The most common forms of learning curves measure improvement in the cost of a given technology from a power function of e.g. cumulative installed capacity or output (Equation 1). The learning effect of cumulative capacity or output on cost improvement is then, generally, expressed as a learning rate measured in terms of percentage cost reduction for each doubling of the cumulative generation capacity or production (Equation 2).

$$c = \alpha * Cap^{\varepsilon} \tag{1}$$

$$LR = 1 - 2^{-\varepsilon} \tag{2}$$

where:

- c      unit cost (£/KW or £/KWh)
- Cap    deployment (cumulative capacity or production, etc.)
- $\varepsilon$     learning elasticity
- LR     technology learning rate

Although the concepts of learning curve has been known for a long time, the pressing need for innovation in energy and environmental technology and policy analysis has been an important source of recent interest for their application to this area. Since 1990,

learning curves have attracted considerable interest for the purpose of technology and policy analysis and in particular for application to energy technologies (Papineau, 2006; McDonald and Schrattenholzer, 2001; Criqui et al., 2000; IEA, 2000).

Also, technology learning rates have been used in important official policy documents. For example, the UK Government's Energy Review (DTI, 2006) and in particular the Stern Review of the economics of climate change (HM Treasury, 2006) have included assumptions regarding technology learning rates in their long term cost projections. Learning rates are as important for technology analysis as discount rates are for cost-benefit analysis. However, moving from the application of learning curves to manufacturing and production activities and applying them instead to innovation and technological progress is a significant step that requires attention to the nature and determinants of innovation. It is, therefore, important to assess the potential and limitations of learning curves as an analytical tool in energy technology and policy analysis.

There is also significant interest in analysis of the potential and promise of new technologies: which are likely to achieve most progress in terms of performance improvements and/or cost reductions? With the objective of improving the efficiency of learning processes. Further, it is important to determine whether resources allocated to promotion of technologies are better spent on research and development (R&D) or capacity promotion policies.

In this paper we assess the current status of learning curves, as applied to energy technologies, and discuss their strengths and weaknesses for energy policy analysis and modeling.

## **2. Learning curves and technical change**

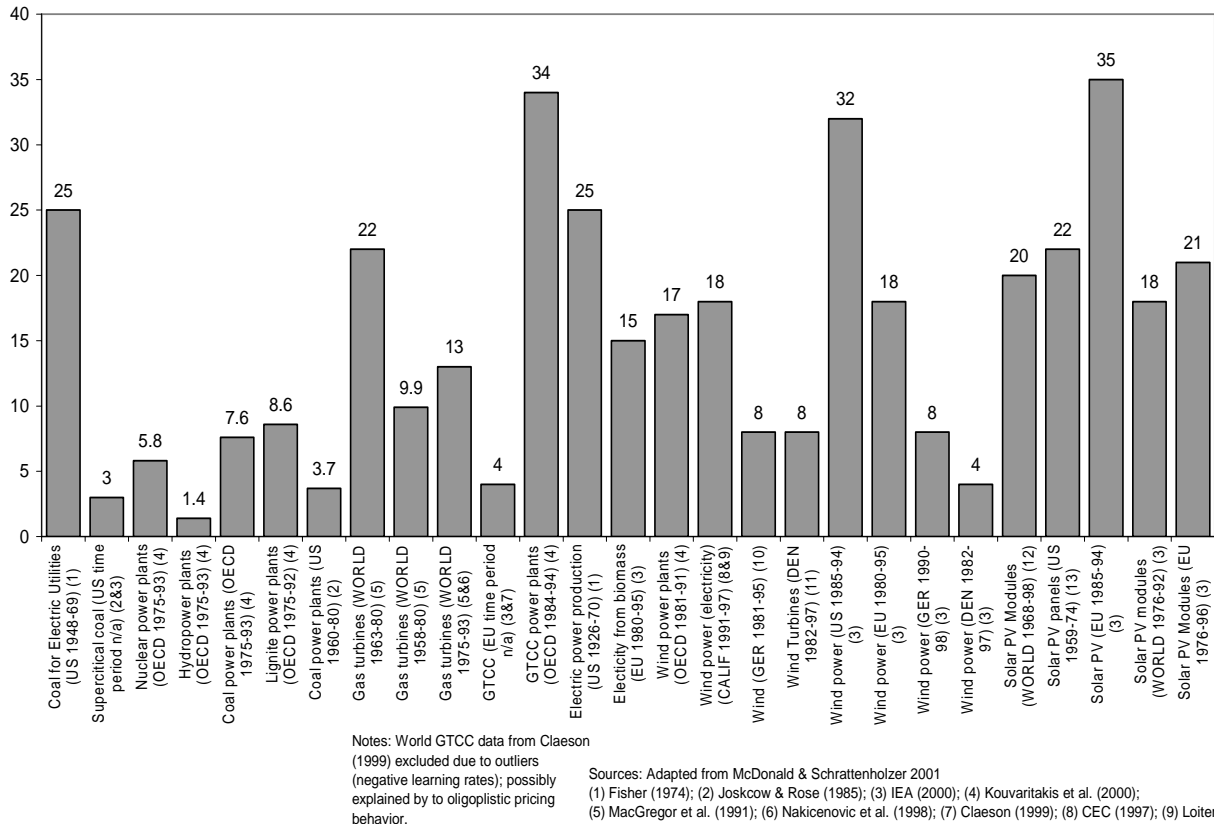
### **2.1 Empirical evidence on learning rates of electricity technologies**

The literature on experience curves frequently summarizes observations in terms of a single parameter – the 'learning rate'. Argote and Epple (1990) survey the literature in manufacturing which go as far back as studies by Wright (1936) on aircraft production in the 1930s and by Rapping (1965) on shipbuilding. Positive experience curves have been found both in manufacturing and service sectors. Recent contributions to this literature

consider the learning processes that lead to experience curves e.g. Thornton and Thompson (2001) for shipbuilding. Furthermore, it extends the idea to production processes e.g. Jaber and Guiffrida, (2004) for reductions in defects and in current industries, and Hatch and Mowery (1998) for new industries such as semiconductors. Argote and Epple (1990) draw attention to the considerable variability in learning, not only across industries, but even within different plants of the same company. Variability is also observed in studies of international technology diffusion and its effects on growth in different countries (Keller, 2004). Dutton and Thomas (1984), quoted in Argote and Epple (1990), provides a frequency distribution of progress ratios (% cost reduction for a doubling of cumulative output) for 108 cases, with a range of 55% to 96% for the progress ratio and a case where the ratio is over 100%, i.e. where costs increase with cumulated output. The mode of this distribution is 81-82%, which has led to the common assumption of an 80% progress ratio i.e. a 20% reduction in unit cost/doubling of output.

A summary of surveyed literature quantifying experience curves in the energy sector is presented in Figure 1. The literature dates back at least to the early 1980s (Zimmerman, 1982; Joskow and Rose, 1985). The great majority of published learning rate estimates relate to electricity generation technologies. As illustrated in Figure 1, estimates associated with different technologies and time periods span a very wide range, from around 3% to over 35% cost reductions associated with a doubling of output capacity. Negative estimates have even been reported for technologies when they have been subject to costly regulatory restrictions over time (e.g. nuclear, and coal if flue gas desulphurization costs are not separated), and for price-based (as opposed to cost-based) learning rates in some periods reflecting aspects of market behavior.

For many technologies, learning rates appear higher in earlier stages. Thus early coal development (US 1948-1969) showed rapid learning in contrast to later evidence (US 1960-1980). Gas turbine data also suggest some evidence of learning depreciation (either kinked or smooth). However, wind energy has demonstrated a wide range of learning rates with no obvious pattern across locations or even time periods (early versus late development stages). Solar PV in general has enjoyed faster rates of learning than other renewable technologies. Grübler et al. (1999), IEA (2000) and McDonald and Schrattenholzer (2001) survey the evidence for energy technologies, showing that, in line with the more general results mentioned earlier, unit cost reductions of 20% associated with doubling of capacity has been typical for energy generation technologies, with the exception of nuclear power.



**Figure 1: Learning rates in electricity production technologies**  
**Source: Köhler et al. (2006)**

This learning rate literature has led, in some cases, to the use of a general “rule of thumb” learning rates of 20%. This is a plausible proxy of the observed rates for many electricity generation technologies, but the evidence on the decline of learning rates over time suggests it may err on the high side, if treated generically across these technologies as a constant in long-run modeling exercises. Indeed, the application of such learning rates has led to cost reductions so high that some studies have artificially imposed a ‘floor price’ to prevent technologies like wind energy from becoming absurdly cheap, which then changes the effective assumed average learning rate.

## 2.2 The implications of the adoption of learning curves

The incorporation of learning curves can significantly change the estimates of costs of stabilisation and policy conclusions, compared to earlier models. Grubb et al. (2002) find that several (but not all) studies incorporating induced technical change suggest that it

could make addressing climate change—including atmospheric stabilization—quite cheap in the long run. Practically all estimates, including the results of the MARKAL modelling work (DTI, 2003), show the effects would rise from a low level today to a range of 0-2% of world GDP by 2050 (Leach et al., 2005). In terms of GDP output lost, this represents a maximum cost of a loss of one year's growth in 2050, i.e. the modelled output in 2050 would not be reached until 2051, in a context in which GDP is likely to have risen by two to three hundred percent in most economies by this date. Other recent surveys confirm these results (Grübler et al., 1999; Azar and Dowlatabadi, 1999), depending on the success of innovation in reducing the costs of low-carbon energy options.

However, the results depend on other features of the models besides the incorporation of learning curves (Barker, Köhler and Villena, 2002). Grubb et al. (2006) and Edenhofer et al. (2006), considering the results of the Innovation Modelling Comparison Project (IMCP), find that if major technological advances are projected to occur anyway in the base case, ITC makes little difference to already “modest” costs. If models have enough technological detail to allow substitution of higher by lower carbon options in supply and responsiveness to the economic signals that enables the lower carbon supplies to “break through” in markets at large scale, this can lead to structurally different energy systems becoming established with various economies of scale now applying to low carbon instead of high carbon systems. ETC can then have a large impact. However, overall the IMCP studies also emphasize that the global economic impact of stabilization targets depends not just on technology, but also upon the nature of the assumed macro-economic linkage between the energy sector and the rest of the economy. These can either ameliorate or exacerbate the costs incurred within the energy sector as a whole.

Edenhofer et al. (2006) find that the main economic mechanisms that drive ITC are:

- the level of ETC in the baseline,
- first-best or second-best assumptions and model structure (CGE, optimal growth, macroeconomic, energy sector bottom up),
- long-term investment decisions and assumptions about foresight and
- prices of backstop and end-of-the-pipe technologies.

As Köhler et al. (2006) note, an important assumption in an experience curve regards floor costs. The conventional experience curve is a declining exponential, hence in order to prevent costs from tending to zero in the long run, many models have to specify a ‘floor cost’ for each curve. In the long run, the process of switching to new technologies

will tend to a set of stable values for technology shares. These relative shares are determined by the relative floor price assumptions (as well as availability for non-backstop technologies), independent of learning rates. Thus, in the long run, a static equilibrium solution may emerge, even in these non-linear dynamic models.

Grubb et al. (2002) discuss the policy implications of these new results. Far more attention should be given to technical change, while induced technical change greatly broadens the scope of technology-related policies. Efficient responses may involve a wide mix of instruments targeted to spur market-based innovation in relevant sectors and broader mitigation policies including economic instruments. It may not be optimal to equalize marginal costs in each period because the returns of learning by doing will differ between sectors and technologies. Endogenous technical change usually increases the benefits of early action, which accelerates development of cheaper technologies. This is the opposite of the result from models with autonomous technical change, which can imply waiting for better technologies to arrive.

Numerical studies of CO<sub>2</sub> abatement imply that for action taken at present, the benefits associated with endogenous technical change may be substantially larger than the direct Pigouvian benefits of CO<sub>2</sub> abatement. If climate change mitigation induces improved technologies in the industrialized nations, it is likely that these technologies will diffuse globally. This will result in a positive spillover that will offset the negative spillover usually hypothesized to result from the migration of polluting industries. Empirical data and analytic understanding are still extremely weak in this area. However, preliminary studies suggest that this effect may dominate over time, which will result in overall negative leakage (i.e., reductions in industrialized countries may also result in reduced emissions in the rest of the world) because of the enormous leverage potentially exerted by global technology diffusion over decades.

Grubb et al. (2006) argue that to the extent that technological change is driven by learning-by-doing, it still does not necessarily follow that emission caps are the only or best way of stimulating this, particularly for some of the less advanced technologies. Such instruments do increase the general prospect of profiting from innovation in low carbon technologies, but a far wider range of market-based policies may be required to stimulate the kind and degree of investment sought.



### **3. Theory-Informed Models of Technology Learning**

While learning curves estimate the correlation between cumulative experience with a technology and falling costs, questions remain as to the causal links between experience and costs. Indeed, the literature on experience curves has little discussion on theoretical explanations although the innovation literature thoroughly examines increasing returns in manufacturing evident from decreasing costs of production which are observed as an experience curve in a firm.

As noted, single-factor learning curve models exhibit shortcomings when applied to technology learning. These models can be improved upon by aligning them with basic features of technical change and innovation theory.

A typology of policies, consistent with the invention-innovation-diffusion paradigm divides these into technology push and market pull policy measures. The aim of technology push is to promote the knowledge base of evolving and emerging technologies through R&D (learning by research effect). There are parallels between the process of technical change and R&D. Basic research broadly refers to the invention stage of a technology. Applied research and development activities are related to the innovation stage. Commercialisation refers to diffusion stage of technical change. The distinction is useful for formulation of technology support policies. The relative importance of R&D in technical progress can vary in different stages of development of a technology. The conventional view is that, at early stages of development, much of technical progress is likely to be achieved through R&D. As the technologies mature, the market mechanisms and commercial incentives play an increasingly important role in further progress of technologies. However, R&D activities can be subject to three main types of market failure namely indivisibility, uncertainty, and externalities (Ferguson and Ferguson, 1994).

Government support for R&D is generally regarded as more important at the basic research and development stage where market failure is more likely to occur. Public support for early-stage R&D can therefore be characterised as public good. Evidence suggests that a public good view of government R&D support in energy technologies is stronger than in many other industries. For many sectors of the economy, broad public R&D combined with patent protection may be adequate to span the innovation chain. In pharmaceuticals, for example, the ‘public good’ (which is largely a private benefit) of better medicines is automatically matched by the large-scale purchase of better drugs by

national health authorities, private health practices, or direct private purchase, while patenting of discrete, chemically-unique drugs provides strong protection for the manufacturers. Thus the 'market pull' forces reach deep into the innovation chain. For the information technologies, product differentiation built on a strong base of publicly-funded basic research provides a similarly strong combination. The way in which some of these basic principles of innovation play out in practice varies radically between different sectors. Information technology and pharmaceuticals, for example, are both characterized by high degrees of innovation, with rapid technological change financed by private investment amounting typically to 10-20% of sector turnover (Neuhoff, 2005). This is in dramatic contrast with power generation, where a small number of fundamental technologies have dominated for almost a century and private sector RD&D has fallen sharply with privatisation of energy industries to the point where it is under 0.4% of turnover (see Margolis and Kammen, 1999; Jamasb and Pollitt, 2005).

In turn, market pull measures are devised to promote technical change by creating demand and developing the markets for new technologies. As the technology matures policies market pull will gradually be more effective in promoting technical progress. The experience gained in the process of manufacturing and operation of technologies through leaning-by-doing is a source of technological progress. Growth in installed capacity remains limited until cost reduction and/or policies improve commercial viability. Commercial prospect and supportive policies encourage capacity expansion, which in turn lead to further cost reduction. As the technology matures the effect of R&D and capacity will decrease.

However, the above characterisation of the role of R&D versus capacity deployment at different stages of technical progress is yet to be firmly established by empirical evidence. At the same time, while model specification plays a crucial role in estimation of learning rates, this has rarely received formal treatment in the literature. Söderholm and Sundqvist (2003) is a notable exception in discussing econometric aspects of learning curves. It is important to study the relative importance of technology push and market pull factors and, in particular their role in different stages of technological development (see Grübler et al., 1999). This will not only enhance our understanding of the stages and process of technical changes but also will help to formulate better informed and targeted technology policies.

Some recent studies, have suggested that learning models should be extended to include learning by researching as R&D contributes to technical progress by enhancing the

knowledge base. The effect of R&D on cost improvement can be accounted for in “two-factor learning curves” that incorporate cumulative R&D spending, or alternatively the number of patents, as proxy for the stock of knowledge. Two-factor learning curves were first proposed in Kouvariatakis et al. (2000) using cumulative R&D and cumulative production as drivers of technology cost improvement. Despite their relative advantages, however, there are few examples of application of two-factor learning models for technology analysis. Klassen et al. (2002) and Cory et al. (1999) apply two-factor learning curves to wind power technology. Miketa and Schratzenholzer (2004) and Barreto and Kypreos (2004) have used two-factor learning curves in bottom-up optimization models of energy technologies.

Inclusion of R&D in learning models adds a controllable or policy variable to the model and reduces the problem of omitted variables bias that would attribute some of the effect of cost reduction by R&D to capacity deployment instead (Söderholm and Sundqvist, 2003). In addition, learning rate estimations need to take into account endogeneity of capacity deployment on the unit cost of technology - i.e. diffusion results in unit cost reduction which in turn encourages capacity promotion policies and market uptake. A simultaneous equations model with capacity and R&D as well as endogeneity of capacity on cost transforms single-factor models from partial empirical functions into learning-innovation-diffusion models that conform to basic elements and feedback of technical change process and invention-innovation-diffusion paradigm.

Söderholm and Klassen (2003) use simultaneous learning and diffusion equations to estimate the effect of promotion policies for wind energy in the UK, Spain, Denmark, and Germany. The study finds significant positive diffusion effect from cost reduction on cumulative capacity as well as the effect of the type of promotion policy on cost development of wind power. Jamasb (2007) uses simultaneous systems equations to a set of electricity generation technologies at different stages of development. The results show that single-factor learning curves overestimate the effect of learning by doing in general and that of new and emerging technologies in particular (Table 1).

The study also indicates that R&D tends to be generally more effective in reducing the cost for technologies in different stages of development. Moreover, the paper finds significant diffusion effect for several of the technologies examined. Finally, the study finds low substitution possibility between R&D and capacity for most of the technologies examined.

	<i>Technology</i>	<b>Learning By Doing Rate – Two-Factor Curves</b>	<b>Learning by Doing Rate – Single-Factor Curves</b>
1	Pulverized fuel supercritical coal	3.75%	4.8%
2	Coal conventional technology	13.39%	15.1%
3	Lignite conventional technology	5.67%	7.8%
4	Combined cycle gas turbines (1980-89)	2.20%	2.8%
	Combined cycle gas turbines (1990-98)	0.65%	3.3%
5	Large hydro	1.96%	2.9%
6	Combined heat and power	0.23%	2.1%
7	Small hydro	0.48%	2.8%
8	Waste to electricity	41.5%	57.9%
9	Nuclear light water reactor	37.6%	53.2%
10	Wind - onshore	13.1%	15.7%
11	Solar thermal power	2.2%	22.5%
12	Wind – offshore	1.0%	8.3%

**Table 1: Learning by doing rates using single-factor curves**

### *Limitations of learning curves*

Despite their recent popularity and potential areas of application, there are important conceptual and practical limitations in the use of learning models for energy technology policy analysis. Although learning curves are used for forecasting technical change and policy analysis they are essentially rooted in the historical development of technologies. Therefore, before leaning curves may be used for predictive technology analysis, it is important to ensure that they reflect the main tenets of their past progress. It is particularly important to note that emerging technologies typically evolve through several stages of development. Therefore, from a theoretical point of view, the future development path of technologies is likely and even expected to be somewhat different from their progress in the past.

The above discussion touches upon the inherent difficulties in modelling issues and our limited understanding of the technology innovation process. As discussed, two-factor leaning curves and incorporating endogeneity of cumulative capacity will go some way in improving the specification of learning models and aligning them more closely with basic features of innovation theory. In addition, there is the important issue of the lack of accurate and detailed data, e.g. in many instances in the form of relatively short time-series. In the long-run, the quality and availability of suitable data may only be improved through allocation of resources and sustained co-ordinated international cooperation.

Applying experience curve data in modelling projections through the use of a single implied 'learning rate' is prone to the exaggeration of effects. The strongest reason for applying them in long-run modelling is not that these issues have been resolved, but rather that the evidence for *some* degree of experience-based cost reduction is overwhelming. Assuming a learning rate determined exogenous is problematic and there remains little consensus on the 'genuine' learning rate – only that zero, the implicit assumption in models that do not incorporate endogenous change, is a number that we can be most confident is wrong. Learning rates are valid but incomplete data, which need to be better explored, but not ignored, in economic analyses of technology (Köhler et al., 2006).

It is important to emphasize that technology and innovation policy cannot be entirely built upon learning curves. Grubb et al. (2006) argue that to the extent that technological change is driven by learning-by-doing, it still does not necessarily follow that emission caps are the only or best way of stimulating this, particularly for some of the less advanced technologies. Such instruments do increase the general prospect of profiting from innovation in low carbon technologies, but a far wider range of market-based policies may be required to stimulate the kind and degree of investment sought.

Grubb et al. (2002) discuss that while induced technical change greatly broadens the scope of technology-related policies, efficient responses may involve a wide mix of instruments targeted to spur market-based innovation in relevant sectors and broader mitigation policies including economic instruments. It may not be optimal to equalize marginal costs in each period because the returns of learning by doing will differ between sectors and technologies.

#### **4. Learning Curves for a Low-Carbon Electricity Sector**

The electricity sector accounts for a significant share of global carbon emissions. Therefore, achieving a low-carbon economy is highly dependent on significant emissions reductions in the sector. However, achieving this objective in the long-term is only possible through innovation and developing new technological solutions. This section discusses specific issues in the use of learning curves as a tool in technology and innovation policy in the context of achieving a low-carbon electricity sector.

As low-carbon technologies are at early stages of development, they should ideally be analysed using suitable learning models that reflect the main factors that drive their progress i.e. R&D and capacity deployment. As discussed earlier, where possible, two-factor learning curves incorporating both capacity deployment and R&D can be used. The two-factor learning models can also be extended to reflect the effect of cost improvement on diffusion of technologies (see Jamasb, 2007).

Technical change can be promoted by combining capacity deployment and R&D according to their relative effectiveness at a given stage of development. Jamasb (2007) shows while the relative importance of R&D in relation to capacity deployment or visa versa may be strong, the substitution possibility between these is generally small and hence there is a need for using both but in proportion to their relative effectiveness in achieving technical progress.

Learning curves can help in analysis of allocation of scarce resources for innovation. Jamasb et al. (2006) discuss that the UK spends substantial, and increasing, amounts of public funding to promote renewable energy sources and contrast these to public energy R&D spend which is only a fraction of the former. Learning curves could help in analyses of whether the funds earmarked for technology promotion are allocated in proportion to their relative effectiveness. At a more aggregate level, learning curves can also be used for allocation of innovation resources among alternative technologies. For example, from a technology policy view, it is useful to distinguish among technologies that can competitively contribute to the resource mix in the medium term versus long term and allocate innovative resources among these accordingly.

The role of individual countries in promoting a technology, whether through R&D or deployment, is rather limited. A related issue then is whether other countries will also engage in innovative activities and whether there is a high degree of spillover and transferability of learning and across countries. Therefore, international collaboration based around common interest in specific technologies will be useful. Also, formal collaboration among countries also reduces the incentive for free riding and can increase the total level of effort.

Learning curves can also be used to estimate the total required investment on R&D and capacity support for bringing the cost of a technology down to a given level. Where the time horizon for technical progress is long, using the present value of the required investment facilitates comparison of alternative spending scenarios or across

technologies. Despite their apparent usefulness, empirical analysis of required investments in learning are, however, not common yet. For example, Neuhoff (2005) measures the total required learning investments for solar photovoltaic technology. The results estimate the required learning investments in capacity for the 2005-23 period under the base scenario at 20 billion euros. The study also shows that the present value of benefits of cost reduction from the learning investments for the 2005-40 period to be 15 times higher than the investments.

The estimates of required capacity deployment to reduce the costs of a technology through learning to a given level may need to be set against the technical potential and availability of resources. For example, if analysis implies that the required capacity deployment is too large and not feasible then alternative approaches such as focus on R&D or international collaboration can be considered. In addition, given the constraints for capacity expansion, it will be possible to estimate the time that each doubling of the capacity is likely to take.

Where estimation of the learning potential of a specific technology may not be possible, analysis of comparable technologies may be used as guide. Rubin et al. (2004) estimate the learning by doing rates of 11 percent for sulphur dioxide and 12 percent for nitrogen oxide control technologies. The study then uses these estimates to assess the learning potential for the carbon capture and sequestration (CCS) technology. These estimates are then fed into a large scale model of the energy sector to calculate estimated benefits of technical progress in CCS in reducing the cost of carbon mitigations for the energy system.

Endogenous technical change usually increases the benefits of early action, which accelerates development of cheaper technologies. This is the opposite of the result from models with autonomous technical change, which can imply waiting for better technologies to arrive. Numerical studies of CO<sub>2</sub> abatement imply that for action taken at present, the benefits associated with endogenous technical change may be substantially larger than the direct Pigouvian benefits of CO<sub>2</sub> abatement. If climate change mitigation induces improved technologies in the industrialized nations, it is likely that these technologies will diffuse globally. This will result in a positive spillover that will offset the negative spillover usually hypothesized to result from the migration of polluting industries. Empirical data and analytic understanding are still extremely weak in this area. However, preliminary studies suggest that this effect may dominate over time, which will result overall in negative leakage (i.e., reductions in industrialized countries may also

result in reduced emissions in the rest of the world) because of the enormous leverage potentially exerted by global technology diffusion over decades.

It is also important to note that there is potentially a degree of interdependence among the projections for different technologies. Achieving the projected cost reductions by integrated large-scale models for several technologies simultaneously may, in practice, due to funding limits or technical constraints, not be possible.

## **5. Conclusions**

The notion of learning curves was first introduced in the context of manufacturing industries in the 1930s. However, in recent years, the need for new energy and environmental technologies in recent years has been an important source of interest in their application to economic analysis of technology innovation and policy. In the climate economy literature, the incorporation of increasing returns to scale due to spillovers and learning are major recent innovations. The concepts of induced technical change and learning curves imply that the direction and rate of technical progress and the stages in the innovation process can be influenced. It then follows that policies can be devised to mitigate market failure for evolving and emerging technologies.

The fundamental policy lesson of the learning curve literature is that while low carbon technologies are more costly than the current dominant technologies; if there is investment in the new technologies, they will become cheaper more rapidly than the current technologies. The cheapest technology pathway in the medium to long term is, however, not a priori clear. The incorporation of learning curves can significantly change the estimates of costs of stabilisation and policy conclusions, compared to earlier models. Several (but not all) studies incorporating induced technical change suggest that it could make addressing climate change—including atmospheric stabilization—quite cheap in the long run.

The use of learning rates for technology analysis in recent policy documents such as the Stern Review underlines the need for a critical assessment of the use of learning curves in technology analysis. The choice of learning models or simply assumed learning rates can have significant effect on the outcome of an analysis. The importance of learning rates for economic analysis of technology can be compared with that of discount rates in cost-benefit analysis. Therefore, the choice of learning models and rates and the results of



these should be treated with care. Simple measures such as the use of alternative models or sensitivity analysis of results can be useful for this purpose.

In relation to the invention-innovation-diffusion paradigm, single-factor learning curves amount to leaving out the effect of R&D on technical change as well as the main aspect of technology diffusion - i.e. the effect of cost reduction on higher technology adoption. The effect of cumulative capacity on the unit cost of technology as in single-factor learning by doing models is only a secondary effect of technology diffusion. Therefore, single-factor learning curves are not suitable for analysis of technologies that are in early stages of progress. A possible response to these shortcomings is to extend learning models to include R&D expenditures in addition to capital investment. This approach has only been undertaken in few studies. There is also a lack of suitable data to estimate such learning models, especially for the new technologies.

There is a need for more research into the nature of the real effects and processes that learning curves tend to capture. As discussed earlier, whether or the extent to which learning curves capture the factors they appear to be measuring (i.e. learning by doing and research), the effect on resulting policy recommendation can be as significant as choosing between a wait-and-see approach versus extensive early actions to curb climate change.

There are several possible directions for future applications of learning models. Given the importance, though not well understood, of spillovers in technological development and diffusion, international R&D co-operation and collaboration can benefit innovation and increase the rate of technological progress. Learning models can be used to analyse the effect of international policy co-ordination and pooling R&D resources or capacity deployment initiatives in order to accelerate technical progress. Another potential area is to assess the potential for improvement in specific technology cost components.

The accuracy of the estimated learning rates remains a major issue. Cross-technology analysis can help to increase confidence in estimated learning rates. Also, the literature suggests that application of learning curves to energy technologies is predominantly focused on electricity generation technologies. In principle, it is possible to apply learning curves to other important energy-related technologies. For example, the use of learning curves in analysis of environmental and clean technologies has been very limited. Technological progress in these areas can have significant cost and qualitative implications for conventional generation technologies. Similarly, application of learning

curves to electricity networks and energy storage technologies is almost absent in the literature. A notable exception has been hydrogen-related studies.

Finally, learning curves may need to seek answers to a slightly different type of policy questions. Instead of assessing the effect of a doubling of cumulative capacity or R&D on unit cost of a technology, it may sometimes be useful to ask short term questions such as, how much increase in these measures can achieve the next, for example, 5 or 10 percent cost reduction. In addition to being more realistic than long-term predictions, such simple conversions of learning rates have also the benefit of allowing comparison of required support for achieving a given percentage of cost reduction across different technologies.

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